An Artificial Trading System

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Abstract

The classical approach to the modelling of complex dynamics systems is to use mathematical techniques such as differential equations to approximate observed global behaviours. For some systems, this approach is inadequate. An artificial trading system is specified using simple rules to conduct trade between entities which are represented using adaptive computational paradgims. Evolution is used to develop the entities, which compete to gain wealth. The global dynamics produced by the interaction of the individual strategies can be studied, to gain an insight into the behaviour of real trading systems, and of complex dynamic systems in general. The system provides a test-bed for experimentation on adaptive computational paradigms.

1. Introduction

This paper describes the design of an artificial trading system. The trading system is intended to facilitate research on a number of levels. First, into the dynamics of actual trading systems (although the model is extremely simplified). Second, into the dynamics of complex adaptive systems in general, and the behaviour of such systems under the influence of evolutionary change. Third, as a test-bed for adaptive computational paradigms, and for the evolution of these paradigms. The model is intended to make integration and comparison of various paradigms possible.

Recent studies in complex adaptive systems have suggested a new approach to the analysis of such systems. In this approach, the researcher attempts to reproduce the global dynamics of the system as an emergent phenomenon from the locally defined rules governing the behaviour of individual entities in the system [Langton, 1989]. This contrasts with the classical approach of producing models (typically using differential equations) which approximate to the observed behaviour under restrictive conditions. Observing the emergence of global dynamics, one can gain insight into the local processes which cause the global behaviour. For example, [Kauffman and Johnsen, 1992), conducting simple experiments on the evolution of competing computer programs, observed the phenomenon of *punctuated equilibria*: long periods of slow evolution followed by sudden extinction events and new speciation within a period of rapid evolution. A similar pattern exists in the fossil record, and it has generally been assumed that the extinction events were due to large-scale natural disasters (such as meteor strikes); these results suggest that such catastrophic events may be a normal consequence of basic evolutionary dynamics.

Economics is an ideal field of study for this approach [Holland and Miller, 1991; Nottola et. al., 1990]. Stock markets, for example, demonstrate dynamics which often seem to defy prediction. If simple artificial markets can be defined which demonstrate some of the key behaviours of real markets (for example, booms and crashes), then we may gain insight into what causes these phenomena, and how they may be alleviated, controlled or responded to. We tend to assume that the complexity of market behaviour is a consequence of the large numbers of variables in the system; however, complex behaviour can be generated by very simple underlying systems, so it may be the case that market dynamics can be explained in terms of only a few particularly significant variables. The general philosophy is to explain rather than to predict, and there is a strong suspicion (motivated by the findings of chaos mathematics) that prediction is actually impossible.

An artificial trading system is also an ideal test-bed for the development of evolutionary programming paradigms. The concept of fitness is well-defined - a good trader makes money, so fitness is equivalent to wealth. The system is largely self-contained, generating by its own action the large amounts of data needed to train entities such as neural networks. There is also evidence than competing against a changing opposition in a closed system causes more robust and fitter entities to evolve (Hillis, 1992), due to the constant adaptive pressure which is applied. Finally, the trading system allows the adaptive capabilities of different paradigms to be compared very effectively, since different types of entities can compete with one another in the same market.

2. The basic trading system

The trading system provides an extremely simple model of a stock trading market. The market consists of a number of entities (also called traders) which have two types of holding: capital and stock. Both are continuous variables, so entities may hold fractional amounts of stock and money. Capital bears interest at a set rate, while stocks pay out a dividend at a variable rate. The traders may buy and sell stocks, the price of which is determined by their own bids. Hence, we may state loosely that the function of the market is to determine a 'correct' price for the stock.

The most difficult design decisions concern the mechanism used to accept and resolve trading bids. Most real markets include specialists through whom the normal traders conduct business (e.g. brokers, auctioneers, and even bookies!). These specialists may take a cut of each transaction, or risk their own capital in some fashion (adding a profit margin), or a combination of the two. Since the artificial trading system must support actual exchanges of stock and capital, in must in some sense fulfil this role. The question is: how much structure should the system impose on the mechanism used by the traders to make exchanges? One aim of the research is to allow 'real' behaviours to emerge, driven by the dynamics of the trading process. Any structure imposed cannot evolve, which encourages us to seek for minimal solutions. On the other hand, we should not expect too much of our traders, which are modelled using quite simple computational paradigms. We may decide to impose a well-defined trading mechanism, where the traders do not have to learn the most basic behaviours (such as how to conduct a negotiation), in order to study higher level effects, such as price trading strategies. Given this background, a range of options may be identified:

- Minimal structure. The trading system provides mechanisms that allow money and stocks to be ceded to other traders, and messages to be passed. The traders must develop their own mechanisms for negotiation, and to handle cheating. Extremely demanding!

- Fixed barter model. The trading system mechanism allows entities to communicate with each other, and to exchange stocks and capitals using a well-defined cheat-proof mechanism. Global market dynamics, if any, arise from this barter system.

- Centralised system. The trading system acts as a broker or auctioneer. All bids are cleared through a central mechanism. The central mechanism may itself be controlled by an adaptive program, or may be defined in some suitable fixed fashion.

The trading system designed belongs in the last category. Some researchers have experimented with artificial double-blind auctions [Rust et. al., 1992], which allow the traders to set the price by a process of centrally moderated negotiation. This system is somewhat more structured. On each trading cycle the traders are each issued with a bulletin of information about the state of the market. They must then construct bids, which essentially specify how many stocks they are willing to buy or sell at any given price. The central mechanism mediates

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[1] It would be pointless to vary the interest rate, as it is the ratio of interest rate to dividend which is significant.

these bids to determine which traders are sellers and which are purchasers; stock and capital are then exchanged. The exchange phase is followed by allocation of dividends and interest, after which the bid phase is re-entered. A set number of trading cycles are followed, the fitness of the traders is evaluated, and evolutionary techniques are used to produce a new pool of individuals. Trade, evaluation and breeding form an entire epoch in the system; over many epochs, the system evolves more sophisticated behaviour. See figure 1.

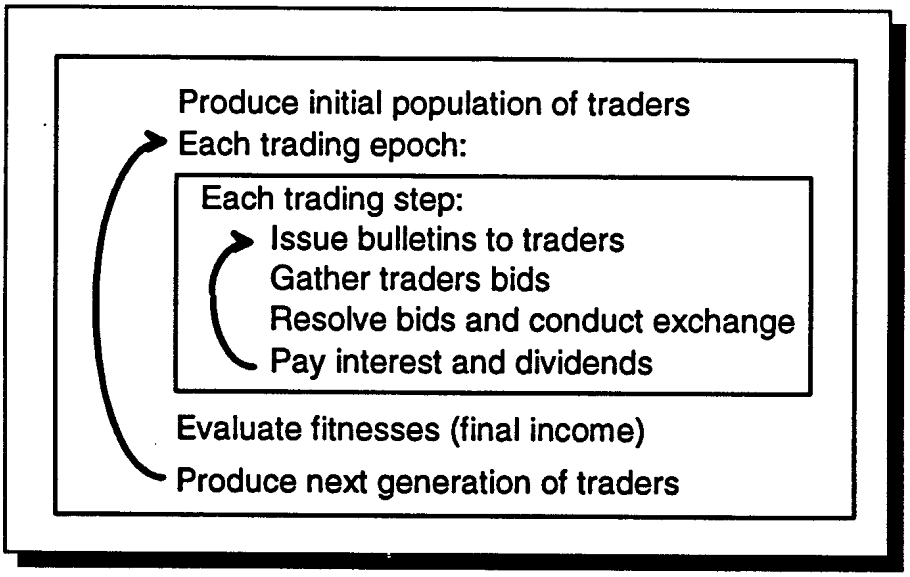

Figure 1: trading system execution cycle

3. Bids and price determination

The central part of the trading system is the mechanism which takes bids and mediates them to cause exchange of capital for stock between sellers and purchasers. Two important questions must be answered: what consists a bid; and how are these bids mediated? Since the trading system allows only a single bid from each trader before conducting exchange, the bid must be sufficient to allow the system to determine what the trader wishes to do at any given price. In other words, the bid must essentially consist of a personal demand curve for the trader. The curve need not be complicated, and actually a very simple step function has been chosen. Curiously, it would actually be easier to construct a trading system where the traders bid using a more 'complex' curve, since the discontinuity of the step function makes it difficult to fix a price. However, it was felt that a more mathematical approach was unjustifiable: human traders certainly do not bid using carefully constructed continuous mathematical functions, and we might easily impose the results that we hope will emerge freely by choosing the function appropriately. The step function has the benefit of being simple enough to understand that it could be conceived of as usable in a real trading system.

Several versions are supported. In the most complicated, the bid consists of a maximum purchase price, a minimum sale price (greater than the maximum purchase price!), a maximum sale quantity and a maximum purchase quantity. Essentially, the bidder is stating a willingness to purchase at up to a given price, to sell above another price, giving associated quantities at the same time. Given that the dividend is always positive and that the traders are rational, we may assume that anybody will buy stock at price zero, and nobody will sell at that price[2]. At price zero, therefore, demand is at a maximum and supply is zero. As price increases, demand falls off and supply rises. The point at which the two cross is selected as the 'market price'.[3] This version of the system is called the 'double bid'. It may be simplified by using a fixed quantity bid rather than a variable amount, in which case it is called the 'fixed double bid', in contrast to a 'variable double bid'. A further simplification is to bid with a single quantity, which can be interpreted directly as the trader's estimate of the value of the stock. If the market price is lower then the trader will wish to purchase; if it is higher, then the trader will wish to sell. This is the 'single bid', which can also be conducted with or without an accompanying quantity - the simpler version being the 'fixed single bid'.

Once a market price has been determined from the supply and demand curves of the traders, the actual exchange must be conducted. This presents another quandary, for we may make each individual transaction at one of two prices: the price bid by the entity, or the market price.

Exchanging at the market price offers certain attractions: using it means that the amount of capital and stock in the system remain constant, and the market clears at a set, identifiable price. Both these features are intuitively appealing. However, there are powerful disadvantages. Let us suppose that the 'true value' of the stock is X, and market sentiment consistently sets a price at $Y > X$. This market scenario favours sellers; that is, those who bid to sell at prices $\leq Y$. However, it makes no distinction between those who bid far below Y and those who bid close to it: thus, there is only weak pressure to assess the best trading price. The market can be dominated by freebooters who happen to bid on the right side of what is essentially a binary market.

The alternative is to exchange at the amount entities bid. This has certain consequences. First, entities which make extremely poor bids (offering to sell very cheap or to buy very high) are heavily penalised. Thus, selection pressure is quite high.[4] Second, capital is actually lost from the market - the system allows buyers to pay it more than it in turn pays out to sellers. This is a relatively benign influence, however: we may regard it as the system extracting a brokerage fee.

The two types of exchange are referred to as the 'mediated' and 'brokered' strategies - in the mediated bid, the system mediates a single price; in the brokered system, it conducts trade and extracts brokerage fees. Taken together with the double/single bid and fixed/variable quantity dichotomies, there are eight variants of the trading system supported.

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[2] Actually, it is not unusual for traders to evolve which refuse to buy and/or offer to sell at price zero! However, they tend to be short-lived.

[3] The supply and demand curves are both discontinuous step functions, so they may not actually meet at *any* value. In this case a 'market price' is set where supply *nearly* equals demand.

[4] Although it still does not push heavily to trade at the 'true' value. The most profitable strategy is to trade at the market price, buying or selling according to whether it is lower or higher than the 'true' value. This is, of course, also true of real markets.

4. Measuring the fitness of traders

In order to use evolutionary techniques to improve the performance of traders, a measure of fitness must be provided - that is, a measure of how effective their trading strategies have been. This is provided by conducting trade for a number of time steps, then calculating the wealth of each entity. Wealth is equivalent to fitness.

Wealth may be measured in a number of ways. The most obvious measure is to calculate the total value of the entities' holdings: *capital* + *stock* × *price*. However, this measure is flawed since the stock price is determined by the traders themselves. If the stock is currently overvalued, then stockholders will be assigned an unreasonably high wealth rating, which is actually illusory.[5] A more useful measure is *final income*: this is the yield in interest payments and dividends which the entity can expect from its holdings after the last time step: *dividend* × *stock* + *capital* × *interest*. The final income is based on exogenous factors only, so it cannot be manipulated by the traders.

Given this measure of wealth (which is equal to fitness), we can define the *true value* of the stock at time step i, V_i, to be the unit price at which traded stock yields the same contribution to the final income as holding the equivalent capital.

Given that the dividend paid on the j^{th} time step is d_j, and representing the final dividend (which is used in the calculation of the final income) as d_{N+1}, we may calculate the true value V_i as follows:

A single unit of stock contributes d_j in dividend at time step j. By the action of compound interest, the contribution of this dividend to the final capital holding is:

$$(1+I)^{N-j}d_j$$

The contribution to final income made by a unit of stock held from time step i to the end of trading is therefore given by:

$$d_{N+1} + I\sum_{j=i}^{N}(1+I)^{N-j}d_j$$

A unit of capital held over the same period would yield $I(1+I)^{N-i+1}$ in final income, so the value of the stock at time step i is given by:

$$v_i = \frac{d_{N+1} + I(\sum_{j=i}^{N}(1+I)^{N-j}d_j)}{I(1+I)^{N-i+1}}$$

In the simple case where the dividend is fixed, $(d_j = d_{N+1},\ \forall j)$ this expression simplifies to $v_i = \frac{d_{N+1}}{I}$ - that is, the true value is the ratio of the dividend to the interest rate. Speaking

[5] The same effect may be observed in real stock markets, and may partially account for the phenomena of 'booms'.

loosely, we can say that in the general case the true value is the ratio of the compound weighted average of the outstanding dividends to the interest rate.

Taking a benign view of the function of stock markets, we may say that the purpose of the market is to estimate the true value of the stock given limited information, and to adjust the trading value to equal the true value (or, at least, to the best available estimate of the true value). As exogenous factors vary the dividend rate, the true value changes and the market price follows it. We may judge the functional efficiency of the stock market by how well it performs this task.

5. Implementation of traders

The traders are (possibly) adaptive agents that make bids based upon information about the state of the market, in an attempt to maximise their final incomes. Information about the market comes in the form of a bulletin each time step. The bulletin may contain various potentially useful pieces of information; for example:

- the last dividend paid (or 'estimated true value' - dividend / interest)
- the entity's current stock holding
- the entity's current capital
- the entity's current income
- the interest rate
- the last market price
- the first derivative of the market price
- the second derivative of the market price

The total information available to an entity therefore consists of the set of bulletins received in trading. The entities must take this input information and produce a bid as an output. Taking a game-theoretic view, the most general description of an entity is as a function which maps all possible values of the sequence of bulletin variables to a set of bid values: $f(B_1, B_2, .., B_t)$. We may refer to any particular such function as a *trading strategy*. The mapping may actually be produced using a variety of computational paradigms:

- Fixed strategy. The entities are constant bid values - the bulletin information is ignored. This is the simplest implementation of an entity, and is used for certain baseline experiments.

- Function approximation. Since a trading strategy can be expressed as a function, we may attempt to model this function directly. For simplicity, it is likely that only the current bulletin will be used to provide input parameters. The function can be modelled using any appropriate technique: for example, polynomial approximation or spline functions.

- Program. Each entity is a computer program which takes a bulletin as input and produces an output. Evolutionary programming has been widely explored in the literature [Koza, 1992]. A simple form of evolvable 'program' has been developed for use in the trading system. See section 6.

- Classifier systems. This is a computational paradigm based upon genetic algorithms [Booker et. al., 1989]. Classifier systems learn by example, and can adapt to a wide range of tasks. Not surprisingly, they are also well-suited to evolutionary development.

- Neural networks. This paradigm has enjoyed enormous popularity in the research community in the last few years. A three-layer neural network can approximate any function, and so is suited to the modelling of strategies. Neural networks can be adapted by learning from example, and a wide literature exists on the application of evolutionary techniques to neural networks [Hunter, 1994].

6. The expression evaluator paradigm

This is a highly simplified version of an evolvable program, which is capable of producing arbitrarily complex arithmetic expressions. The evaluator consists of two parts: a vector of values and a list of arithmetic expressions. The vector is used to pass input values in, output values out, and to provide constants and temporary variables. The expressions are binary arithmetic expressions of two vector elements, the result of which is used to set another vector element. To execute an evaluator the input values (taken from the bulletin) are inserted into the appropriate points in the vector, the expressions are evaluated in turn, and the outputs are extracted from the appropriate points in the vector. See figure 2.

Expressions	Vec. No	Vector
v4=v2+v8	0	0
v6=v0×v1	1	1
v8=v2÷v5	2	2
v3=v3+v4	3	<input>
v6=v7–v5	4	<input>
v8=v3–v1	5	-3.4 <output>
v5=v8+v3	6	1.6 <output>
	7	12.1
	8	6.3

Figure 2: A sample evaluator

7. Implementation of evolution in the trading system

There is a large body of research on evolutionary techniques in the literature, and many different forms of genetic operators exist: Evolutionary Programming [Fogel et. al., 1990], the Genetic Algorithm [Holland, 1975], Genetic Programming [Koza, 1992]; rank-based genetic algorithms [Whitley and Kauth, 1988] . Which of these methods is most appropriate depends on the type of entities being evolved; given new paradigms, none of them may be appropriate. For example, specialised versions of the genetic operators were introduced for the expression evaluator paradigm to reflect its peculiarities. However, a standard public domain package (libGA100) has been integrated, which can support the following features: the genetic algorithm with bitwise mutation, crossover, elitism, and rank-based evaluation. In addition, the system supports Gaussian mutation. All evolutionary parameters are soft-coded into a configuration file and can be easily adjusted.

8. Preliminary experiments

A number of early experiments have been conducted, using the fixed strategy and expression evaluator models. In all of these experiments the dividend is fixed throughout the trading period. The expected behaviour is that the market will determine a price corresponding to the true value of the stock, $D \div I$. This is indeed the case, provided that the evolutionary parameters are selected appropriately.

In the first experiment fixed strategies are evolved. This is the simplest version of trading possible. With appropriate evolutionary parameters, the traders evolve so that the market price reflects the true price. Both the single and double bid systems have been tested. With the single bid, the system settles down to the extent that the market price perturbs from the true value only slightly (less than one percent), and trading virtually ceases. In the double bid system the entities quite rapidly evolve to buy at below the true value, and to sell at above it. However, the pressure is then quite weak to converge these two values, and the market price may perturb more strongly within the region around the true value where little or no trading takes place. In both cases, it is fair to say that the market quickly discovers the true value.

The need for 'appropriate evolutionary parameters' has been mentioned. In some early experiments the bids and market price increased without limit! This appears to be because mutant entities appear which made absurdly high bids. These mutants are purged on the next generation; however, their high bids drag the market price up sufficiently to allow other high bidding (but less extreme) entities to prosper. These high bidding entities themselves produce extreme mutants in the next generation who continue the process by sacrificing themselves to elevate their relatives. In effect, a 'species' of traders evolve which exploits a weakness in the market system to advance itself. This runaway effect can be curtailed by lowering the mutation rate and mutation variance, which prevents sufficient extremists arising to make the joint strategy successful. A more useful change is to replace uniform with Gaussian mutation, which substantially cuts the proportion of extremists produced. This is indicative of a general effect which the designer of artificial dynamic systems must be aware of: the tendency of co-operative behaviour to develop. For example, it is conceivable that in a market system with sufficiently complex entities, species could develop which act in concert to 'rig' the market price and to benefit from this. The emergence of such behaviour is a fascinating study in itself, but can be quite destructive if undesired. This experiment demonstrated that such co-operation can emerge even between extremely simple entities in an extremely simple system, yet its appearance can be very hard to predict or even to detect.

The fixed strategy experiments were conducted with both variable and fixed bid quantities. It was discovered that in the variable quantity case, the quantity bid tended to increase without limit. Given two entities with equal, profitable bid prices, we can see that the entity which bids the higher quantity will make more profit, and thus become fitter. The converse is true if the entities have equal, bad bid prices, but then both will almost certainly be purged from the population. The net pressure is therefore to bid for as great a quantity as possible. Essentially, there is no mileage in caution! In later experiments, the fixed quantity was used for this reason.

The fixed dividend experiments were also repeated using the expression evaluator, which is capable of far more complex behaviour than the fixed strategy. The results produced were essentially the same: the system converges to the true value after a number of generations.

9. Future experiments

Having established that that the system behaves as expected with extremely simple entities and conditions, the next step is to introduce more challenging conditions, then to integrate more capable entities. Code has been introduced to allow the dividend rate to be controlled exogenously. One control method supported is the random walk.If the dividend follows a random walk, the best possible estimate of true value is the ratio of last dividend paid to the interest rate. Entities will be given a bulletin which specifies this value and the last market price. Given that the most profitable strategy in an inefficient market is to bid 'near to' the market price, it will be interesting to see whether the entities manage to evolve the stable strategy of bidding the 'true price'.

The following stage will be to introduce a 'news' variable. This will contain a value indicating the likely level of the dividend a few time steps hence. If sufficient time steps remain until the end of trading, this news value is approximately the best estimate of the true value available. By corrupting the news value with different amounts of random noise for each entity (making it unreliable) an additional factor is introduced. The joint knowledge of the market is now greater than the knowledge of individuals, so that the value of following the market price is increased (it gives an indirect measure of the sentiment of other traders). The effect of this 'incomplete information' on the market dynamics will be studied.

Beyond these experiments with the existing system, it may become necessary to build a new system where parallelism can be explored. The current approach has heavy computational costs, even with very simple entities bidding. The clearance mechanism requires a sort on the bid values (to determine the market price), which severely limits the number of entities which can be handled. Typical runs involve one hundred traders over a few hundred generations, and take of the order of five seconds per trading epoch. It is unlikely that markets containing more than a thousand traders could be handled, even running overnight. Parallelism would imply removing the central price setting mechanism. This can be done using coarse or fine grain parallelism. In coarse grain parallelism, a number of machines can run small markets (of perhaps two or three hundred entities), each with its own central price setting mechanism. Wealthy entities are occasionally exchanged between markets. This approach allows a large number of entities to be handled simultaneously, while helping to maintain population diversity. The total number of entities in the market could easily exceed ten thousand, using a network of fifty-plus workstations in parallel. In the fine grain solution, traders are assumed to exist at given positions in some kind of continuum. Trade and selection are both conducted locally - with other entities in nearby locations. This type of market system is far more difficult to design, and probably requires specialised parallel hardware to run effectively.

10. Conclusion

This paper has introduced an artificial trading system. The trading system is designed to allow the analysis of the dynamics of complex systems (and of trading systems in particular), and to facilitate experimentation with adaptive computational paradigms. The results of early experiments are promising, and work continues to provide a more powerful and complete system.

11. Acknowledgements

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